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# Morris method of sensitivity analysis applied to assess the importance of input variables on urban water supply yield – A case study

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SUMMARY

Yield plays a central role in the processes, practices, management and operation of urban water supply systems. Improved accuracy of the yield estimate is important and can be obtained by improving knowledge of important variables. Yield is typically estimated via computational simulation using the entire sequence of available historic climate data. Sensitivity analysis provides a framework and many techniques that can identify important variables in a computational model. Using the Morris method, this paper investigates the importance of input variables used in the estimation of yield of urban water supply systems. The Barwon urban water supply system in Australia is used as the case study. Using a number of climate scenarios of various lengths, sensitivity analysis showed that the security criteria of the Barwon system was the most important to the yield estimate. The upper restriction rule curve also showed notable importance. Significantly the results showed that the use of a single climate sequence for estimating yield would produce misrepresentative results for another climate scenario.


## 1. Introduction

Climate change and the increasing growth in population has put many water resources and supply systems around the world under pressure, often being required to supply a demand which is close to or exceeding the yield of the resource or system (Dawadi and Ahmad, 2012; UNESCO, 2012). Such pressures have been exerted on most Australian water supply systems, resulting in long restriction periods, and in some cases the introduction of permanent water saving measures (DSE, 2004; Byrnes et al., 2006). Demand shortfalls can be alleviated by decreasing the demand via water saving measures and schemes, and education; and/or increasing the yield of the system by optimising system management and/or augmentation with additional water sources. All of these methods, and many operational processes rely heavily on the yield estimate of the water supply system.

McMahon and Mein (1986) define yield as "the amount of water that can be supplied from a reservoir or catchment during a specified interval of time". Additionally, they define safe or firm yield as "the maximum quantity of water that can be guaranteed during a critical dry period". Similarly, Linsley et al. (1992) state yield is "the volume of water that can be supplied from a reservoir or multi-reservoir system over a given duration". They also define the safe, or firm, yield is "the maximum quantity of water that can be guaranteed during a critical dry period". McMahon and Adeloye (2005) provide different definitions to safe yield and firm yield stating firm yield "is a term used mainly in the USA to describe the yield that can be met over a particular planning period with a specified no-failure reliability usually based on the historical record", and expressing that safe yield implies 100% reliability in the supply. They also give a definition of operational yield, which considers seasonal patterns of demand and demand restrictions, and state that it is determined by reducing supply so that reservoirs do not become empty during a prevailing drought and assume no knowledge of future inflows.

Yield is defined in this paper and throughout much of the Australian water industry as: the maximum average annual volume of water that can be supplied from the water supply system subject to climate variability, operating rules, demand pattern and adopted level of service (or security criteria) (Erlanger and Neal, 2005; DSE, 2011). Yield is commonly estimated using an iterative process where the average annual demand is increased until just prior to system failure. System failure occurs when one or more security of supply criteria threshold is violated. The demand at this point is deemed to be the yield of the system under the considered model conditions. The yield estimate is typically

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determined using a computational model of the physical system simulated over the entire available sequence of historic climate data. Numerous simulation software packages are available for estimating yield, such as MODSIM (Labadie et al., 1986) and MODSIM-DSS (Fredericks et al., 1998), IRIS (Loucks et al., 1987), WASP (Kuczera and Diment, 1988). WATHNET (Kuczera, 1992), IQQM (Simons et al., 1996), RiverWare (Zagona et al., 2001), REALM (Perera and James, 2003; Perera et al., 2005), Mike Basin (DHI, 2001) and WEAP (Yates et al., 2005).

The REALM (REsource ALlocation Model) simulation software package is used extensively in the water supply industry in Australia for simulation of water supply systems (Perera and James, 2003; Perera et al., 2005). REALM uses a fast network linear programming algorithm to optimise the harvesting and bulk distribution of water resources within a water supply system. It considers inputs including system configuration details, user-defined operating rules, and system inflows and outflows such as streamflow, evaporation, rainfall and demand data. See Perera and James (2003) and Perera et al. (2005) for further details.

Optimising the management of a water supply system is a continual process largely the responsibility of water authorities and their processes and practices. The estimation of yield is integral in water supply system management, and policy development and enforcement. Not only does the yield define the maximum target demand, it is used in augmentation studies, guides water sharing, and assists in decision-making policies. However, the yield estimate is subject to uncertainty and variability in input variables. The possible perturbation in input variables will propagate through the model and alter the yield estimate. Input variable perturbations will affect the yield differently and therefore carry varying degrees of weighting, or importance, on the yield. Identifying and quantifying the importance of input variables provides insight into which variables to investigate in order to improve the understanding and estimation of the yield. This importance of input variables can be determined through sensitivity analysis.

Sensitivity Analysis (SA), occasionally termed uncertainty propagation analysis (Lei and Schilling, 1994), is the study of the relationship between inputs and outputs of a computational model (Saltelli et al., 2000). It has become an essential element of the development and evaluation of environmental models (Saltelli et al., 2000; Jakeman et al., 2006), providing a powerful framework for use in the development, operation, calibration, optimisation and application of computational models. Given the selection of suitable technique(s) and framework(s), SA can provide information regarding the model structure, the dependence on input variables, the behaviour of the model at extreme values/events, and can be used as a decision making tool. Much literature is available on the theory and applications of SA from various scientific fields [see Frey and Patil (2002), Saltelli et al. (2000, 2004, 2008), Ratto et al. (2007) and references therein]. In a SA, model inputs are perturbed within predefined ranges, representing numerous realisations of the physical system. The model response is observed, with the sensitivity to variation of each input variable indicated by the magnitude of change of the response variable. The range of the input variable perturbation is generally the plausible values, often dictated by, but not limited to, the range of uncertainty of the input variable.

The current paper follows a study by King and Perera (2010) which used the Morris method, the Fourier Amplitude Sensitivity Test (FAST) and the extended FAST methods of SA to study the importance of input variables used in the estimation of yield of a simple case study (VU and DSE, 2008). This case study dealt with an urban water supply system with two reservoirs and a single demand centre. The yield was estimated using REALM, considering a single climate sequence consisting of 28 years of monthly climate data; consisting of streamflow, evaporation, rainfall and climate index. The SA framework adopted in King and Perera (2010) considered 26 input variables identified in the definition of yield, assuming they were subject to only data measurement and handling errors (Type II uncertainty error, as will be discussed in Section 2). The input variables included the system management rules and policies as well as climate data and demand data. System characteristics include the reservoir, pipe and channel, and network details and configuration which are fixed and considered to be well known. Model parameters include the REALM model settings used in the network linear programming algorithm. System characteristics and model parameters were assumed accurate and were not considered in the SA (i.e. Type I uncertainty error, that will be discussed in Section 2, was not considered in this study). Several variable handling techniques were used for input variable perturbations. These were required as many of the input variables had numerical characteristics that could not be simply perturbed by a scalar value. Results of the study showed that the yield of the simple system (VU and DSE, 2008) was highly sensitive to the streamflow variable, with the supply of reliability threshold, the upper restriction rule curve and the consecutive months threshold of subsequent importance.

Several important disadvantages and limitations associated with the SA techniques and framework adopted in King and Perera (2010) were identified

1. *Historic data use* – Yield is generally estimated using a single, historic data sequence consisting of all available data. This approach provides a plausible climate realisation to perform model simulations. However, the use of one sequence and one length results in a yield estimate and set of optimal operating rules that may not be suitable for another other climate realisation or for a different planning length.
2. *Time-series variables* – Yield considered streamflow, evaporation and rainfall time-series data, as well as a climate index which modified average monthly demands to account for climate changes over the simulation period. The perturbation technique used on the streamflow variable simply increased or decreased every data point in the time-series by a percentage that was randomly selected in accordance to the SA technique. In effect this strategy changed the total streamflow volume entering the system with little change to the variability which is not in accordance with the definition of yield. This perturbation strategy was also applied to the evaporation and rainfall time-series.
3. *Climate dependant variables* – Knowing the effect of the streamflow, evaporation and rainfall on the estimation of yield is of little use to water authorities as they are uncontrollable. Furthermore, their cross-correlations should be maintained in the SA since they are closely related; however this was not considered in the perturbation technique used in point 2 above.

The main recommendation drawn from the case study presented by King and Perera (2010) was to separate the input variables used in the estimation of yield into *climate dependant variables* and *system policy variables*, and perform SA on the system policy variables using several climate scenarios. The current study follows this recommendation, considering the Barwon urban water supply system in Australia as a case study. The sources of uncertainty and variation are newly considered, with the two groups of variables related elegantly to two sources of yield variation; (1) natural variability in the climate dependant variables and (2) knowledge deficiency, or uncertainty, of the system policy variables. However, since natural variability cannot be reduced, knowing the importance of the climate dependant variables is not as valuable as knowing the importance of the system policy variables. Therefore the SA framework used studies the importance of the system policy variables explicitly, with the importance of the climate dependant variables assessed through simulation over various climate scenarios.

The SA framework adopted in this paper is to consider multiple climate scenarios of various simulation lengths over which the importance of the system policy variables are determined using SA. This SA framework allows the effect of climate variability and simulation length on the importance of input variables to be explicitly assessed whilst retaining cross-correlations inherent in climate variables and avoiding perturbing the times-series variables. In effect, the framework can then be used to determine if climate variability and/or simulation length affects the importance of the controllable system policy variables used in the estimation of yield. The Morris method of SA (Morris, 1991) was selected for use in this paper as it is a reliable and efficient SA technique, shown to be successful when applied to a water supply system planning model (King and Perera, 2010).

This paper begins by presenting a discussion of the SA framework adopted in this study for water supply systems, followed by a discussion of the Morris method, including application, indices and extensions. A description of the Barwon urban water supply (used as the case study) is then presented including the climate scenario selection, and a discussion of the system policy variables and their methods of perturbation. The SA results are then described. Finally the main findings and conclusions of the paper are summarised with resulting recommendations.

## 2. Sensitivity analysis framework adopted

Sensitivity analysis is the study of how input variable uncertainty and variability propagates through a computational model to its output. The typology and terminology of uncertainty, and the sources of uncertainty and variability can be difficult to define, which Van Asselt and Rotmans (2002) attribute to being the reason that many classifications of uncertainty exist. Walker et al. (2003) attribute the lack of a shared generic typology and common terminology of uncertainty in model-based decision support to the differing viewpoints of stakeholders in the modelling process. Ascough et al. (2008) provide a thorough discussion on various uncertainty typologies present in uncertainty and risk assessment literature from 1990 to 2008. Wheaton et al. (2008) discuss the extensive range of lexicon synonymous to uncertainty and note that through classification, the types and sources of uncertainty can be identified in a systematic fashion. For in-depth commentary of the definitions and typologies of uncertainty, see the recently published: Norton et al. (2006), Refsgaard et al. (2007), Ascough et al. (2008), Wheaton et al. (2008) and citations therein. Indeed, it is the opinion of the authors that there is not, and should not be, a common, shared typology and common terminology. Each field and discipline, each application and stage therein, and each analyst and set of stakeholders will dictate where uncertainty and variability originates, which are deemed important and the potential results of these uncertainties.

Observing uncertainty in light of computational modelling, Burges and Lettenmaier (1975) propose two main types of uncertainty; (Type I) the selection of the incorrect model with correct (deterministic) parameters, and (Type II) the choice of correct model with incorrect (or uncertain parameters). These two types of uncertainty will almost always exist simultaneously. The SA framework applied in the King and Perera (2010) case study assumes the model is an accurate representation of the physical system, removing all Type I uncertainty, leaving only Type II uncertainty. That is, the model was considered a black box, with physical system characteristics such as reservoir and carrier capacities, and internal model operations like REALM's hierarchy of optimisation, accurate and fixed.

Whatever the typology used in a SA application, two distinct types of uncertainty are generally recognised: *objective* uncertainty, relating to natural variability or inherent randomness of a system, and *subjective* uncertainty, relating to the lack of accurate knowledge of the system, its model and variables (King, 2009). As Yen and Ang (1971) note, the objective uncertainty will always exist, even if or when all subjective uncertainty is eliminated. Both Type I and Type II uncertainty (Burges and Lettenmaier, 1975) are subjective uncertainty.

In the context of SA, uncertainty relates to possible variations of an input variable, and therefore variability within a model and its output. A distinction and separation from uncertainty to variability is hereby considered. The two types of uncertainty, *objective* and *subjective*, were considered in the estimation of yield of an urban water supply system in this study, identifying the sources of variability found in the input variables.

The objective uncertainty considered in this study is the *natural variability*, which is the inherent randomness found in certain variables such as climate patterns and climate dependant variables. This type of variability cannot be controlled or optimised, and although future predictions of these variables can be insightful, they cannot be precise. Natural variability in the estimation of yield relates to inherent spatial and temporal trends and patterns that underlay climate events, as well as some further fluctuations caused by randomly occurring events such as extreme weather events (i.e. individual heterogeneity). In this case study, natural variability affects the climate dependent variables: streamflow, rainfall, evaporation and demand.

The second source of variability in the estimation of yield is caused by *knowledge deficiency*. The knowledge deficiency is due to either the uncertainty in the optimum value of input variables or from uncertainty of how the model behaves under alternate variable space regions. Knowledge deficiency exists in the operation of the system and model, including model uncertainty (formulation, numerical, parameter and execution errors), data uncertainty (measurement errors, handling errors and inconsistent sampling), and model and result interpretation. In this study, knowledge deficiency affects the system policy variables consisting of restriction rule curves, security of supply thresholds and target rule curves. These variables primarily form management policies and rules, and they are generally derived through optimisation, calibration, modeller experience, and stakeholder requirements and expectations. The operational positions (i.e. the values used in the management and studies of the system) of these variables are known to the water authority but their optimum positions are relatively unknown as they are subject to the climate sequence over which variable optimisation is performed.

The SA framework adopted in this paper uses the Morris method of SA to determine the importance of system policy variables for each of the selected climate scenarios. The system policy variables consisted of restriction rule curves, security of supply thresholds and target rule curves.

## 3. The Morris method

The Morris method of SA (Morris, 1991) is a specialised randomised One-At-a-Time (OAT) SA design that is an efficient and reliable technique to identify and rank important variables (Morris, 1991; Campolongo et al., 2000, 2007). The assumption of an OAT SA design is that if variables are changed by the same relative amount, the variable that causes the largest variation in the output is the most important. Fig. 1a shows that in a traditional OAT SA design each variable is tested individually, by changing the variable in question between a pair of model simulations. The pairs of model simulations can be considered as experiments. The standardised effect of a positive or negative $\Delta$ change (or step) of an

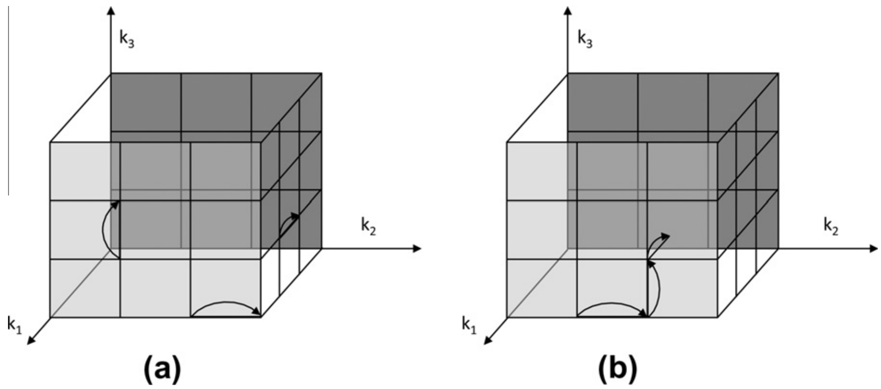



**Fig. 1.** The region of experimentation, Ω. (a) Individual EEs for a three variable model. Six simulations required $p = 4$. (b) Trajectory EEs for a three variable model. Four simulations required $p = 4$.

input variable can be calculated using Eq. (1). This is also known as the Elementary Effect (EE – Morris, 1991). Traditional OAT SA design requires $2k$ model simulations to determine an EE for each of the $k$ input variables.

$$EE_i(\mathbf{x}) = [y(x_1, x_2, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) - y(\mathbf{x})]/\Delta \tag{1}$$

where $\Delta$ is magnitude of step, which is a multiple of $1/(p-1)$; $p$ is the number of 'levels', or values, over which the variables can be sampled. This is also known as the resolution of sampling.

The Morris method uses the same principle of changing each variable one at a time by $\Delta$ but as shown in Fig. 1b, the experiments are arranged so as to create a trajectory through the variable space. Since the experiments share simulation points in a trajectory, the Morris method requires $k + 1$ model parameters to calculate one EE for each of the k input variables. Morris (1991) proposed the use of a series of matrixes to construct each trajectory, which is discussed in Section 3.1. Several trajectories ($r$) are constructed providing r EEs for each of the $k$ input variable. The finite distribution of the EEs attributed to the $i$-th input variable is denoted as $F_i$.

The following section describes how Morris (1991) constructs each trajectory using a worked example, resulting in the trajectory given in Fig. 1b.

### 3.1. Trajectory construction

Consider a $k$ variable model with a region of experimentation, Ω, that has a number of evenly spaced intervals, or levels. The levels, denoted as $p$, set the selectable values that can be sampled for each variable as the set: $\mathbf{x} = \{0, 1/(p-1), 2/(p-1), 3/(p-1), \ldots, (p-2)/(p-1), 1\}$. The magnitude of the experiment step, $\Delta$, is a multiple of $1/(p-1)$. The base values, $\mathbf{x}^*$, are randomly chosen from the set of selectable $\mathbf{x}$ values ranging from 0 to $1 - \Delta$. This range is used so that when $\Delta$ is added to $\mathbf{x}^*$ the subsequent sampling points remain in Ω. The $\mathbf{x}^*$ is not used as a simulation point in the trajectory but is used as a base point for the construction of the trajectory.

Fig. 1b shows a $k = 3$ variable model for which Ω has $p = 4$ levels, $\mathbf{x} = \{0, 1/3, 2/3, 1\}$ and $\Delta = 1/3$ has been selected for the experiment steps. Base value $\mathbf{x}^* = \{1/3, 0, 2/3\}$ have been randomly selected.

Morris (1991) defines the final trajectory matrix, $\mathbf{B}^*$, as given in the following equation:

$$\mathbf{B}^* = (\mathbf{J}_{m,1}\mathbf{x}^* + \Delta\mathbf{B}')\mathbf{P}^* \tag{2a}$$

$$\mathbf{B}^* = (\mathbf{J}_{m,1}\mathbf{x}^* + (\Delta/2)[(2\mathbf{B} - \mathbf{J}_{m,k})\mathbf{D}^* + \mathbf{J}_{m,k}])\mathbf{P}^* \tag{2b}$$

The random directions of the trajectory are determined using $\mathbf{B}'$ as defined in Eq. (3). $\mathbf{B}'$ defines whether changes in the trajectory are positive or negative.

$$\mathbf{B}' = \left(\frac{1}{2}\right)[(2\mathbf{B} - \mathbf{J}_{m,k})\mathbf{D}^* + \mathbf{J}_{m,k}] \tag{3}$$

where $\mathbf{J}_{m,k}$ is a $(m \times k)$ matrix of 1's, where $m = k + 1$; $\mathbf{B}$ is a $(m \times k)$ sampling matrix, containing only 0s and 1s arranged in a lower left triangle unit matrix; $\mathbf{D}^*$ is a $k$-dimensional diagonal matrix which the diagonal elements have an equal probability of taking a value of +1 of −1. The $\mathbf{D}^*$ used to create Fig. 1b is shown below:

$$D^* = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \tag{4}$$

The modified sampling matrix $\mathbf{B}'$ used to create Fig. 1b is shown in Eq. (5). This is then multiplied by the $\Delta = 1/3$ defined earlier, to create Eq. (6):

$$\mathbf{B}' = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix} \tag{5}$$

$$\Delta\mathbf{B}' = \begin{bmatrix} 0 & 0 & 1/3 \\ 1/3 & 0 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 0 \end{bmatrix} \tag{6}$$

The parenthesis of Eq. (2a) used in Fig. 1b is shown as Eq. (7).

$$\mathbf{J}_{m,1}\mathbf{x}^* + \Delta\mathbf{B}' = \begin{bmatrix} 1/3 & 0 & 1 \\ 2/3 & 0 & 1 \\ 2/3 & 1/3 & 1 \\ 2/3 & 1/3 & 2/3 \end{bmatrix} \tag{7}$$

The final permutation matrix ($\mathbf{P}^*$) is a randomly selected $k$-dimensional matrix where each column and row contains only single element equal to 1 and the rest 0's. $\mathbf{P}^*$ is not an essential element of $\mathbf{B}^*$, but the random locations of the 1's changes the order that the variables are perturbed, and increases the number of trajectories possible.

Eq. (7) is multiplied by the $\mathbf{P}^*$ shown in Eq. (8) to create the trajectory matrix, $\mathbf{B}^*$, as given in Eq. (9) and shown graphically in Fig. 1b.

$$\mathbf{P}^* = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \tag{8}$$

$$\mathbf{B}^* = \begin{bmatrix} 1 & 1/3 & 0 \\ 1 & 2/3 & 0 \\ 1 & 2/3 & 1/3 \\ 2/3 & 2/3 & 1/3 \end{bmatrix} \tag{9}$$

Here it can be seen that each column, which represents a variable, is changed one-at-a-time by a negative or positive $\Delta$ = 1/3. Finally, the design matrix $\mathbf{X}$ is constructed of $r$ $\mathbf{B}^*$ matrixes, creating $n$ samples. The columns of $\mathbf{X}$ are scaled to appropriate ranges of the input variables and the model simulations performed. The model outputs of the $n$ samples, the yield estimate in this case, are then used to calculate $r$ EEs for each input variable using Eq. (1).

### 3.2. Morris method indices

The finite distribution of the EEs due to the $i$-th input variable is denoted as $F_i$. Each $F_i$ contains $r$ independent elementary effects (one EE per input variable from each of the $r$ trajectories), from which the sensitivity indices, or importance measures, can be computed. Morris (1991) proposed two measures, namely the mean ($\mu$) and standard deviation ($\sigma$) of the set of EEs for each input variable, while Campolongo et al. (2007) introduce a third index, $\mu^*$, which gives extra information. They are calculated using:

$$\mu_i = \frac{\sum_{n=1}^{r} EE_n}{r} \tag{10}$$

$$\sigma_i = \sqrt{\frac{1}{r}\sum_{n=1}^{r}(EE_n - \mu_i)^2} \tag{11}$$

$$\mu_i^* = \frac{\sum_{n=1}^{r} |EE_n|}{r} \tag{12}$$

The sensitivity index $\mu_i$, calculated using Eq. (9), assesses the sensitivity strength between the $i$-th input variable and the output response due to all first- and higher-order effects that are associated with that variable (Campolongo and Braddock, 1999). When $\mu_i$ is high in contrast to other variables, the output has a high sensitivity to this input variable. Conversely, a variable with a low $\mu_i$ value has small sensitivity associated to it as the same $\Delta$ change causes a relatively low change in output. Eq. (11) is used to determine the spread (variance) of the finite distribution of the $EE_i$ values, which is denoted by $\sigma_i$. It indicates possible interactions with other variables and/or that the variable has a non-linear effect on the output (Campolongo and Braddock, 1999). Campolongo et al. (2007) discuss the use of $\mu^*$, the mean of the finite distribution of absolute values of the $EE_i$, as given in Eq. (12). From here onwards, the subscript $i$ is left out from the discussion in this paper for easy reading.

The index $\mu^*$ provides a 'true' importance measure, free of any non-monotonic input to output behaviour that could be present in $\mu$. That is $\mu^*$ provides the overall sensitivity of the $i$-th input variable void of any cancelling out effects that may be contained in $\mu_i$. The $\mu$ and $\mu^*$ are the accepted sensitivity measures of the Morris method. However, due to the assumed linear input to output relationship, the sparse sampling and low number of model simulations the rankings on $\mu^*$ are more important than the calculated values (Braddock and Schreider, 2006; Ratto et al., 2007). Using $\mu$ and $\mu^*$ together can provide insight into the nature of the non-linearity of the model and input variable.

### 3.3. Improved sampling strategy

A drawback of the original Morris method (Morris, 1991) is that, although randomised, the sampling strategy used by Morris (1991) may not provide sufficient coverage of the variable space, especially when dealing with a large number of input variables. Campolongo et al. (2007) suggest an improved sampling strategy to improve the spread by creating a large number of trajectories; say ~500–1000, and selecting a set of trajectories that results in the greatest 'spread' throughout $\Omega$. Campolongo et al. (2007) showed that considerable improvements in the distribution of the sampled points can be achieved using this strategy. However it was not employed in this study as the distribution of points was not considered an issue due to the small number of input variables used.

### 3.4. Grouping of input variables

Grouping input variables in SA helps to explore the effects of groups of closely related variables, such as the clusters of variables associated with certain processes of a model. For instance, by grouping all variables related to the modelling of restriction rule curves (i.e. upper, lower and base curves, percentages restrictable and relative positions) in an urban water supply simulation model, the synergy of their perturbations on the estimation of yield can be assessed. The synergy of any group of input variables is invaluable to modellers as it signifies that even if individual variables cause little sensitivity, together they might be of major importance. Conversely, if individual sensitivities are large, but combined sensitivity is small, then it indicates some cancelling out, or lessening effects.

The original Morris method (Morris, 1991) has been extended to incorporate grouping of input variables (Campolongo et al., 2007). The grouping of input variables is performed by changing all variables in a given group simultaneously. The EEs now represent a $\Delta$ change of multiple input variables. When considering groups of variables, only $\mu^*$ and $\sigma$ are generally considered as the calculation of $\mu$ is not straightforward when variables in a group are changed in opposite directions (Campolongo et al., 2007).

## 4. Case study

### 4.1. Description of the Barwon system

Barwon Water Corporation is currently the largest regional water authority in Victoria (Australia) supplying water and sewerage services to 275,000 permanent residents over 8100 square kilometres. The region of operation, highlighted in Fig. 2, covers a regional (rural) and coastal area in south-west Victoria, Australia. The operational headworks of the Barwon Water Corporation, hereinafter simply termed the Barwon system, consists of over 5000 km of pipes, six major reservoirs, six water treatment plants and nine water reclamation plants. Water is sourced from two rivers and their catchments, and a number of groundwater sources. Geelong is the only urban demand centre considered in the model. The REALM model of the Barwon system was supplied by Barwon Water Corporation (http://www.barwonwater.vic.gov.au/). and is described in detail in SKM (2006). A conceptual schematic of the Barwon system REALM model can be seen in Fig. 3. This schematic shows only the urban water supply system of the Barwon system. The diversion channel connecting the West Barwon and Wurdee Buloc reservoirs receives water from sources shared with rural (irrigation, stock and domestic or farm dam) and environmental demands. Water is also shared with the rural and environmental demands just downstream of the Lal Lal and Bostock reservoir releases confluence.

Seventy-seven years of weekly historic streamflow, evaporation, rainfall and demand data was available, beginning 1st January, 1927. The streamflow records include inflow into the reservoirs from rainfall-runoff, river diversions and groundwater pumping across the Barwon system. This inflow was derived from a combination of historic measurements, hindcasting and


**Fig. 2.** Region of service of the Barwon Water Corporation. Inset shows the location of Victoria within Australia. (Source: www.maps.google.com).

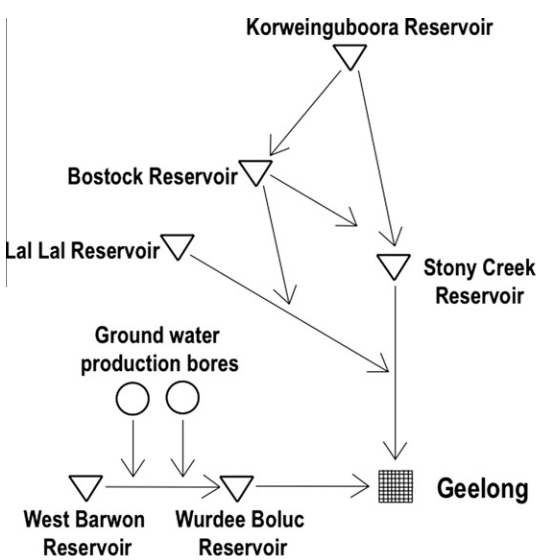



**Fig. 3.** Basic headworks schematic of the Barwon Water system.

calibration. Evaporation and rainfall data for the various reservoirs, used to model the gains and losses of the reservoirs, was also historic data derived through similar measurement, hindcasting and calibration. The unrestricted weekly demand for the Geelong urban demand centre were derived from historic consumption records. The Geelong demand constitutes more than 90% of the total demand from the water sources shared with the rural and environmental demands. Environmental flows are modelled as a fixed volume or according to a minimum flow rule. Due to the low demand and the mandatory nature of the rural and environmental flows in the REALM model they were considered outside the scope of this study.

### 4.2. Selection of climate scenarios

Seventy-seven years of weekly historic data is available from 1927 to 2004 for the climatic dependent variables, i.e. streamflow, rainfall, evaporation and demand. Four simulation lengths were selected (20 years, 40 years, 60 years and 77 years) as an even spread between minimum simulation length considered (20 years) and the maximum possible (77 years). Simulation lengths less than 20 years were not considered robust for water industry and would not properly capture events such as droughts and wet spells.

Five scenarios were selected for the 20 year simulation period based on the ranked total streamflow volumes entering the six reservoirs. The totals were first calculated for each week for the next 20 years (i.e. for $20 \times 52 = 1040$ weeks), until the 52nd week of year 1984. Ranked totals were not considered beyond 1984, since there were no 20 years of data for weeks after the 52nd week of year 1984 during the study period of 1927–2004. These totals were then ranked and five scenarios selected from equally spaced rankings, consisting of the maximum and minimum streamflow volumes (scenarios 1 and 5 respectively) and three intermediate ranked volumes. Fig. 4 shows the weekly streamflow values, the 20 year moving total streamflow volume and the selected scenarios for the 20 year simulation length. Streamflow was used to select the scenarios as it provides a robust representation of climate behaviour. For every streamflow sequence that was selected, the same period of the remaining climate dependant variables (rainfall, evaporation and demand pattern) were also selected so as to maintain cross correlations. The same procedure was used to select five 40 year and five 60 year scenarios. Two additional 20 year scenarios were selected that have a similar total streamflow volume as scenario 2,

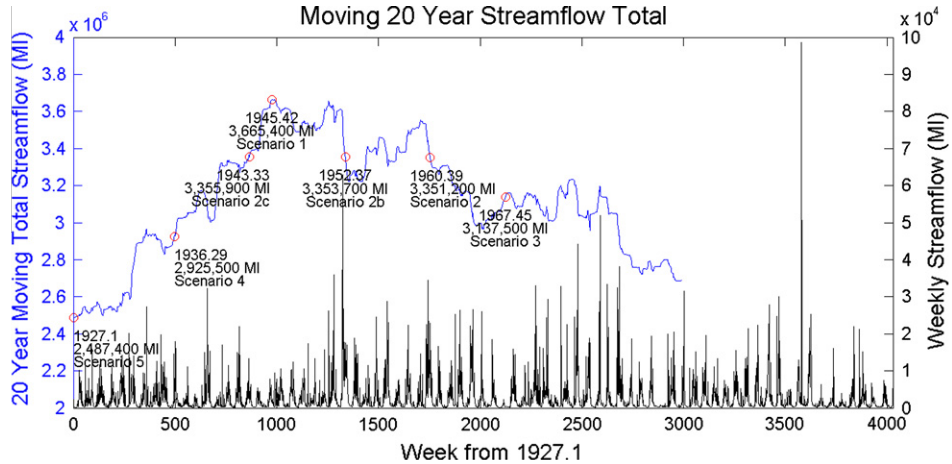



**Fig. 4.** Weekly streamflow and 20 year moving streamflow total. Starting time step is indicated by Year.Week. i.e. 1945.42 represents the 42nd week of 1945.

**Table 1**
Selected scenarios.

| | 20 Year scenarios | | | 40 Year scenarios | | | 60 Year scenarios | | |
|---|---|---|---|---|---|---|---|---|---|
| | Rank | Total streamflow (Ml) | Starting Year.Week | Rank | Total streamflow (Ml) | Year.Week | Rank | Total streamflow (Ml) | Year.Week |
| 1 | 2990 | 3,665,400 | 1945.42 | 1951 | 6,730,400 | 1951.07 | 911 | 9,509,100 | 1939.08 |
| 2 | 2242 | 3,351,200 | 1960.39 | 1464 | 6,600,700 | 1949.17 | 684 | 9,384,300 | 1941.22 |
| 3 | 1495 | 3,137,500 | 1967.45 | 976 | 6,430,200 | 1957.50 | 456 | 9,306,700 | 1940.03 |
| 4 | 747 | 2,925,500 | 1936.29 | 488 | 6,160,200 | 1931.35 | 228 | 9,228,000 | 1930.32 |
| 5 | 1 | 2,487,400 | 1927.01 | 1 | 5,839,500 | 1964.26 | 1 | 9,152,000 | 1928.25 |
| 2b | 2243 | 3,355,900 | 1952.37 | | | | | | |
| 2c | 2244 | 3,353,700 | 1943.33 | | | | | | |

**Table 2**
List of system policy variables, their assigned range and groupings.

| Reference number | Variable | Range | Groupings |
|---|---|---|---|
| 1 | Upper RRC curvature | −10% to +10% Of nominal position | Restriction rule curves |
| 2 | Upper RRC position | −5% to +5% Of nominal position | |
| 3 | Lower RRC curvature | −10% to +10% Of nominal position | |
| 4 | Lower RRC position | −5% to +5% Of nominal position | |
| 5 | Base demand position | 70–76% | |
| 6 | Stage 1 percentage restrictable | 10–20% | |
| 7 | Stage 2 percentage restrictable | 50–60% | |
| 8 | Stage 3 percentage restrictable | 70–80% | |
| 9 | Stage 1 relative position | 20–30% | |
| 10 | Stage 2 relative position | 45–55% | |
| 11 | Stage 3 relative position | 70–80% | |
| 12 | Target storage curves | Discrete distribution 0–10,000 | Target storage curves |
| 13 | Supply reliability threshold | 80–98% | Security of supply |
| 14 | Minimum storage threshold | 4–20% | |

but at significantly different positions in the historic sequence. These are labelled scenario 2b and 2c. The rank, total streamflow volumes and the starting time step of the selected 20, 40 and 60 year scenarios are given in Table 1. Each scenario is identified through the starting time step indicated by Year.Week, i.e. 1945.42 represents the 42nd week of year 1945.

Three 77 year scenarios were selected using a shuffling (or recycled) approach. The 77 year historic sequence is divided into a number of blocks and reordered to produce replicate climate sequences. In this study 11 blocks of 7 years were used. The advantage of this method is that a number of new scenarios of maximum length are easily generated, without generating data using stochastic data generation methods (see Srikanthan and McMahon, 1985, 2001; McMahon and Adeloye, 2005, for discussions and reviews of stochastic data generation methods). It is possible that this approach can break severe droughts or create worse droughts, providing new climate event sequences. A disadvantage is that it breaks serial correlations between six pairs of years at the end and beginning of the blocks; however, the loss of this correlation was considered to be negligible.

As there is little change in total streamflow volume between scenarios 2, 2b and 2c (Table 1) and no volume change in the three 77 years scenarios, these scenarios provide an opportunity to test the importance of input variables due to changes in climate variability without the effects of a volume change of streamflow, rainfall and evaporation. All other scenarios test the effects of different streamflow, rainfall and evaporation volumes and their climate variability. In total, 20 climatic scenarios (i.e. seven 20 year, five 40 year, five 60 year and three 77 year scenarios) are considered in the SA in this study.

### 4.3. Handling of system policy input variables

Three primary system policies and rules control the behaviour of water supply systems and are therefore the primary source of uncertainty leading to variability of yield estimate. These are the Restriction Rule Curves (RRCs), Target Rule Curves (TSCs) and security of supply thresholds, each of which containing several associated individual variables. Table 2 shows the individual variables, with their assigned ranges and groupings that are used in the SA in this study.

#### 4.3.1. Restriction rule curves

A four level Restriction Rule Curve (RRC) policy is used to impose demand restrictions for the Barwon system. As seen in Fig. 5, the RRCs consist of upper, lower and base rule curves as well as intermediate zones that define various percentage demand to be restricted. The upper, lower and base rule curves are expressed as a function of total system storage in megalitres. Nominal positions of the upper and lower rule curves and the percentage restrictable are given in Fig. 5. The nominal position of the base demand curve is 73% Average Annual Demand (AAD) which is the combined value for all months of the year, i.e. (73%/12 months) = 6.1% AAD per month.

When the total system storage is above the upper RRC, no restrictions are imposed. Restrictions are triggered when the total system storage is below the upper RRC at the beginning of a given month. Restriction severity increases as the storage volume decreases. Only the demand above the base demand is restricted (i.e. only ex-house demand is restricted) using the percentage restrictable corresponding to the restrictions zones.

Table 2 lists the 11 individual variables that control the RRC policy and their assigned perturbation ranges. Fig. 6 shows the typical

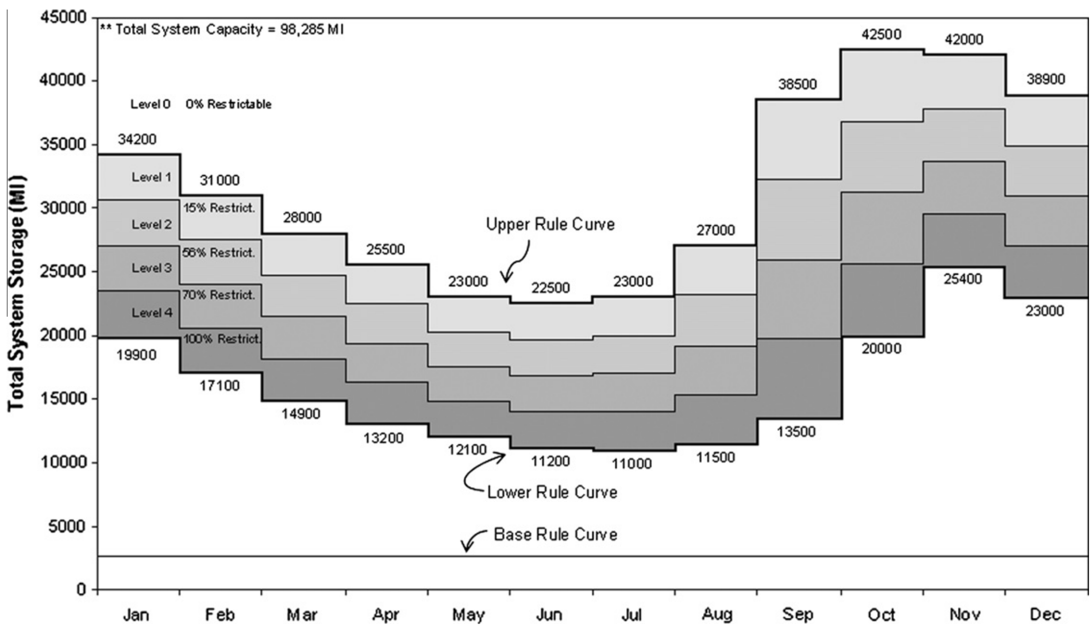
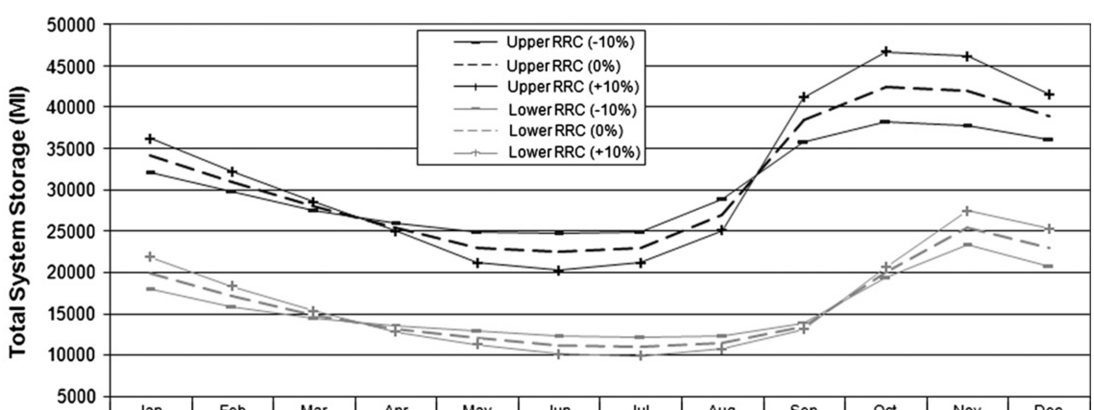



**Fig. 5.** Nominal restriction rule curves showing upper, lower and base curves with respect to total system storage.




| | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Upper RRC (-10%) | 32148 | 29760 | 27440 | 26010 | 24840 | 24750 | 24840 | 28890 | 35805 | 38250 | 37800 | 36177 |
| Upper RRC (0%) | 34200 | 31000 | 28000 | 25500 | 23000 | 22500 | 23000 | 27000 | 38500 | 42500 | 42000 | 38900 |
| Upper RRC (+10%) | 36252 | 32240 | 28560 | 24990 | 21160 | 20250 | 21160 | 25110 | 41195 | 46750 | 46200 | 41623 |
| Lower RRC (-10%) | 17910 | 15903 | 14453 | 13596 | 12947 | 12320 | 12100 | 12305 | 13905 | 19400 | 23368 | 20700 |
| Lower RRC (0%) | 19900 | 17100 | 14900 | 13200 | 12100 | 11200 | 11000 | 11500 | 13500 | 20000 | 25400 | 23000 |
| Lower RRC (+10%) | 21890 | 18297 | 15347 | 12804 | 11253 | 10080 | 9900 | 10695 | 13095 | 20600 | 27432 | 25300 |

**Fig. 6.** Upper and lower restriction rule curves, including the upper and lower bounds for perturbation of curvature.

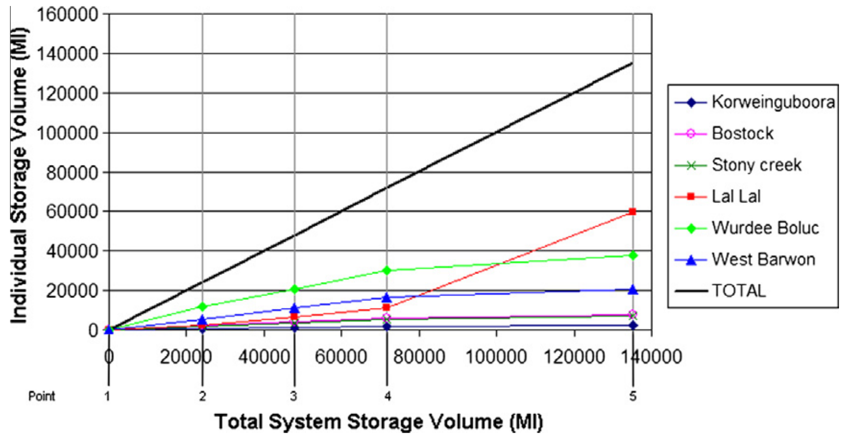



**Fig. 7.** Target storage curves showing six main operating reservoirs and total storage curves.

**Table 3**
Morris method importance indices for individual input variables – 20 year scenarios.

| Morris index | Variable | Scenario | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 2b | 2c |
| $\mu$ | Relative position 1 | −208 | 158 | −108 | −159 | −141 | −50 | −94 |
| | Relative position 2 | −63 | −98 | −66 | −78 | −45 | −7 | −10 |
| | Relative position 3 | −1 | −27 | −389 | −53 | −28 | −25 | −219 |
| | Percentage restrictable 1 | 150 | 115 | 58 | 162 | 71 | 104 | 143 |
| | Percentage Restrictable 2 | 39 | 10 | 661 | 182 | 25 | 42 | 157 |
| | Percentage restrictable 3 | 41 | 401 | 84 | 20 | 13 | 63 | 18 |
| | Upper RRC curvature | −2954 | −2221 | −555 | −1299 | −1073 | −797 | −1374 |
| | Upper RRC position | −6177 | −3306 | −355 | −1541 | −1176 | −3744 | −2265 |
| | Lower RRC curvature | 140 | 75 | −487 | 112 | 154 | 106 | 110 |
| | Lower RRC position | 53 | 98 | 682 | 83 | 82 | 42 | 148 |
| | Base demand | −240 | −240 | −956 | −398 | −388 | −150 | −469 |
| | Target curves | 294 | −312 | −143 | −37 | −132 | −226 | 790 |
| | Minimum level threshold | −2552 | −9862 | −11063 | −4943 | −4610 | −6297 | −3983 |
| | Supply reliability threshold | −13944 | −15585 | −5401 | −7620 | −6488 | −16491 | −11002 |
| $\mu^*$ | Relative position 1 | 251 | 507 | 108 | 216 | 152 | 160 | 269 |
| | Relative position 2 | 82 | 98 | 67 | 147 | 50 | 71 | 90 |
| | Relative position 3 | 1 | 55 | 400 | 86 | 47 | 25 | 258 |
| | Percentage restrictable 1 | 257 | 226 | 91 | 168 | 82 | 134 | 299 |
| | Percentage restrictable 2 | 116 | 114 | 667 | 213 | 123 | 53 | 232 |
| | Percentage restrictable 3 | 108 | 472 | 84 | 84 | 48 | 63 | 159 |
| | Upper RRC curvature | 3679 | 2460 | 1129 | 1712 | 1621 | 1658 | 2023 |
| | Upper RRC position | 6367 | 3941 | 599 | 1729 | 1489 | 3858 | 2581 |
| | Lower RRC curvature | 157 | 129 | 754 | 268 | 209 | 154 | 279 |
| | Lower RRC position | 100 | 98 | 682 | 110 | 104 | 91 | 191 |
| | Base demand | 284 | 518 | 1000 | 449 | 416 | 287 | 503 |
| | Target curves | 1699 | 2193 | 930 | 1116 | 575 | 1526 | 1610 |
| | Minimum level threshold | 2552 | 9862 | 11063 | 4943 | 4610 | 6297 | 3983 |
| | Supply reliability threshold | 13944 | 15585 | 5401 | 7620 | 6488 | 16491 | 11002 |
| $\sigma$ | Relative position 1 | 539 | 2385 | 269 | 380 | 294 | 418 | 623 |
| | Relative position 2 | 393 | 343 | 192 | 311 | 164 | 236 | 248 |
| | Relative position 3 | 10 | 273 | 2601 | 236 | 129 | 155 | 843 |
| | Percentage restrictable 1 | 482 | 853 | 227 | 248 | 205 | 264 | 670 |
| | Percentage Restrictable 2 | 306 | 339 | 4211 | 392 | 262 | 156 | 443 |
| | Percentage restrictable 3 | 262 | 2220 | 186 | 235 | 140 | 172 | 422 |
| | Upper RRC curvature | 3166 | 2510 | 1922 | 1621 | 1502 | 2070 | 2203 |
| | Upper RRC position | 3810 | 3875 | 1071 | 1518 | 1439 | 2889 | 2938 |
| | Lower RRC curvature | 477 | 320 | 4244 | 419 | 373 | 361 | 503 |
| | Lower RRC position | 276 | 364 | 4209 | 240 | 218 | 281 | 503 |
| | Base demand | 407 | 972 | 4302 | 591 | 372 | 613 | 761 |
| | Target curves | 2332 | 3310 | 1254 | 1541 | 709 | 1903 | 2046 |
| | Minimum storage threshold | 5865 | 15007 | 9044 | 6097 | 5561 | 11751 | 7337 |
| | Supply reliability threshold | 4953 | 11233 | 8380 | 4474 | 4628 | 8804 | 5767 |

operating position (provided by the Barwon Water Corporation) and the values of the upper and lower RRCs (used in the SA). The solid lines show the upper (+) and lower (−) limits of the RRCs when perturbed via the RRC curvature variables. The upper and lower RRCs are controlled by two variables. Both variable's range was assigned with expediency to the system, study and handling procedure. The ±10% indicated as the limits are the maximum deviation from the operating levels at the highest and lowest points.

**Table 4**
Morris method importance indices for individual input variables – 40 year scenarios.

| Morris index | Variable | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu$ | Relative position 1 | −50 | −73 | −26 | −70 | −137 |
| | Relative position 2 | −62 | −65 | −65 | −70 | −66 |
| | Relative position 3 | −41 | −45 | −39 | −46 | −67 |
| | Percentage restrictable 1 | 45 | 74 | 98 | 36 | 107 |
| | Percentage restrictable 2 | 89 | 20 | 67 | 23 | 74 |
| | Percentage restrictable 3 | −667 | 149 | 878 | 78 | 90 |
| | Upper RRC curvature | −547 | −185 | −423 | −1232 | −48 |
| | Upper RRC position | −1092 | −327 | −966 | −2203 | −238 |
| | Lower RRC curvature | 139 | 111 | 48 | 32 | 114 |
| | Lower RRC position | 62 | 124 | 84 | 187 | 224 |
| | Base demand | −328 | −740 | −915 | −340 | −1000 |
| | Target curves | 202 | −221 | −19 | 351 | −827 |
| | Minimum level threshold | −17777 | −14610 | −16306 | −6941 | −9183 |
| | Supply reliability threshold | −5951 | −4885 | −5560 | −12927 | −4919 |
| $\mu^*$ | Relative position 1 | 220 | 166 | 97 | 103 | 179 |
| | Relative position 2 | 73 | 67 | 65 | 124 | 66 |
| | Relative position 3 | 58 | 45 | 82 | 52 | 90 |
| | Percentage restrictable 1 | 118 | 166 | 357 | 146 | 116 |
| | Percentage restrictable 2 | 176 | 110 | 111 | 114 | 163 |
| | Percentage restrictable 3 | 879 | 179 | 889 | 102 | 92 |
| | Upper RRC curvature | 1025 | 644 | 838 | 1559 | 688 |
| | Upper RRC position | 1337 | 1118 | 1204 | 2354 | 1080 |
| | Lower RRC curvature | 206 | 154 | 205 | 137 | 200 |
| | Lower RRC position | 87 | 135 | 118 | 249 | 224 |
| | Base demand | 550 | 768 | 1316 | 413 | 1000 |
| | Target curves | 880 | 799 | 865 | 1258 | 915 |
| | Minimum level threshold | 17777 | 14610 | 16306 | 6941 | 9183 |
| | Supply reliability threshold | 5951 | 4885 | 5560 | 12927 | 4919 |
| $\sigma$ | Relative position 1 | 610 | 515 | 239 | 253 | 367 |
| | Relative position 2 | 190 | 169 | 148 | 453 | 206 |
| | Relative position 3 | 168 | 136 | 228 | 154 | 257 |
| | Percentage restrictable 1 | 283 | 520 | 1324 | 345 | 228 |
| | Percentage restrictable 2 | 533 | 334 | 344 | 208 | 306 |
| | Percentage restrictable 3 | 5364 | 414 | 4780 | 230 | 222 |
| | Upper RRC curvature | 1638 | 908 | 1211 | 1491 | 910 |
| | Upper RRC position | 2510 | 2368 | 2271 | 2130 | 1437 |
| | Lower RRC curvature | 343 | 324 | 384 | 377 | 362 |
| | Lower RRC position | 200 | 454 | 276 | 523 | 351 |
| | Base demand | 632 | 2159 | 5034 | 586 | 805 |
| | Target curves | 1780 | 1504 | 1868 | 1656 | 750 |
| | Minimum storage threshold | 14247 | 10542 | 12442 | 10691 | 5130 |
| | Supply reliability threshold | 9237 | 7303 | 8308 | 8009 | 6373 |

Variables 1 and 3 change the shape of the curves, making them either steeper (+) or flatter (−) against the total system storage. For example, if variable 1 was randomly assigned +10%, then the upper RRC curve would assume the sleeper (+) solid line. If it were assigned −5% then it would assume a position midway between the dashed line and the lower, flatter (−) solid line. Variables 2 and 4 shift the positions of the upper and lower RRCs with respect to the total system storage within the range assigned. The relative position variables (variables 9, 10 and 11 in Table 2), the percentage restrictable variables (variables 6, 7 and 8 in Table 2) and base demand position (variable 5) are all scalar percentages that are perturbed within the range given in Table 2 using conventional perturbation methods. Note that the percentage restrictable in zone four is not perturbed and is set at 100%.

### 4.3.2. Target storage curves

Target storage curves regulate the volume of water in individual storages at a given total system storage. They specify the preferred storage volume of individual storages for a given total system storage volume (Perera and Codner, 1996). The Barwon system supplies water to the Geelong City from six reservoirs. The target storage curves distribute the total system storage to the six reservoirs using a five-point curve as shown in Fig. 7. These curves were provided by the Barwon Water Corporation. At each of the five points given in Fig. 7, the individual storages must sum to the total system storage. The individual storage curves must not decrease as the total storage increases. This characteristic means that conventional perturbation cannot be performed. Instead, 10,000 sets of target storage curves were randomly generated and assigned a 1–10,000 discrete sampling distribution for use in the SA of this study. These sets were generated ensuring that individual storage volumes summed to the required total system storage and that the individual volumes of reservoirs do not decrease as total system storage increases.

### 4.3.3. Security of supply

The two security of supply criteria used in the Barwon urban water supply system are the supply reliability threshold and the minimum storage threshold. The system is deemed to have failed when one or more threshold is violated. The threshold that causes system failure is later referred to as the critical threshold.

The supply reliability threshold limits the number of time-steps that restrictions are imposed on the ex-house demand. It is measured as the ratio of the number of simulation time-steps without restrictions imposed to the total number of simulation time-steps in the period used in the simulation model, and was nominally set at the generally accepted industry standard of 95% (Barwon Water, 2007). This variable was assigned a range of 80–98% in this study.

**Table 5**
Morris method importance indices for individual input variables – 60 year scenarios.

| Morris index | Variable | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu$ | Relative position 1 | −86 | −208 | −179 | −111 | −116 |
| | Relative position 2 | −141 | −50 | −84 | −67 | −13 |
| | Relative position 3 | −46 | −92 | −82 | −35 | −14 |
| | Percentage restrictable 1 | 37 | 145 | 134 | 97 | 67 |
| | Percentage restrictable 2 | 76 | 99 | 100 | −37 | −9 |
| | Percentage restrictable 3 | 65 | 111 | 112 | 311 | 72 |
| | Upper RRC curvature | −230 | −189 | 123 | −221 | −438 |
| | Upper RRC position | −1020 | 333 | 134 | −505 | −895 |
| | Lower RRC curvature | 128 | 121 | 104 | 119 | 134 |
| | Lower RRC position | 75 | 256 | 165 | 92 | 53 |
| | Base demand | −844 | −1192 | −929 | −646 | −344 |
| | Target curves | −61 | −748 | −477 | 41 | −108 |
| | Minimum level threshold | −12187 | −11312 | −9836 | −11457 | −12180 |
| | Supply reliability threshold | −5351 | −2621 | −3141 | −5748 | −6021 |
| $\mu^*$ | Relative position 1 | 115 | 208 | 201 | 121 | 116 |
| | Relative position 2 | 181 | 87 | 90 | 70 | 62 |
| | Relative position 3 | 62 | 116 | 82 | 92 | 83 |
| | Percentage restrictable 1 | 86 | 153 | 161 | 103 | 124 |
| | Percentage restrictable 2 | 130 | 170 | 133 | 156 | 121 |
| | Percentage restrictable 3 | 101 | 149 | 118 | 345 | 100 |
| | Upper RRC curvature | 649 | 768 | 451 | 616 | 848 |
| | Upper RRC position | 1286 | 931 | 687 | 756 | 1199 |
| | Lower RRC curvature | 172 | 132 | 151 | 142 | 185 |
| | Lower RRC position | 103 | 256 | 186 | 115 | 95 |
| | Base demand | 855 | 1192 | 929 | 737 | 464 |
| | Target curves | 784 | 855 | 689 | 687 | 781 |
| | Minimum level threshold | 12187 | 11312 | 9836 | 11457 | 12180 |
| | Supply reliability threshold | 5351 | 2621 | 3141 | 5748 | 6021 |
| $\sigma$ | Relative position 1 | 224 | 357 | 325 | 235 | 257 |
| | Relative position 2 | 583 | 232 | 179 | 194 | 167 |
| | Relative position 3 | 157 | 287 | 261 | 262 | 231 |
| | Percentage restrictable 1 | 231 | 272 | 304 | 234 | 269 |
| | Percentage restrictable 2 | 263 | 278 | 250 | 457 | 256 |
| | Percentage restrictable 3 | 201 | 291 | 212 | 1665 | 203 |
| | Upper RRC curvature | 954 | 1183 | 639 | 879 | 1135 |
| | Upper RRC position | 2346 | 1127 | 985 | 1019 | 1789 |
| | Lower RRC curvature | 314 | 308 | 301 | 253 | 315 |
| | Lower RRC position | 208 | 344 | 315 | 245 | 219 |
| | Base demand | 2515 | 867 | 711 | 1714 | 496 |
| | Target curves | 1385 | 766 | 765 | 1138 | 1387 |
| | Minimum storage threshold | 8801 | 4163 | 4394 | 8472 | 9352 |
| | Supply reliability threshold | 7713 | 4898 | 5455 | 7826 | 8203 |

The lower limit was set at a reasonable minimum reliability expected by water users and the upper set to 98%, as 100% would produce very low yield estimates.

The minimum storage threshold sets the limit of total system drawdown that can occur during the simulation. The range for the minimum storage threshold was set to 4–20%. These values were determined via discussion with Barwon Water Corporation and through a preliminary test that found unrealistic yield estimate behaviour occurred when the variables were set beyond these values. Results of this preliminary test are not given in this paper for brevity.

### 4.4. Results

Three sets of experiments were performed: an individual variable experiment and two grouped variable experiments. The variables and associated groupings are given in Table 2. Grouping of related variables was done to gain insight into system behaviour, such as any synergism or cancelling out that may occur. All experiments were performed using a 50 trajectory, eight level ($p = 8$), $\Delta = 4$ Morris design on each of the 20 climate scenarios. Fifty trajectories were deemed to be sufficient to ensure that convergence of SA indices were satisfied, whilst p and $\Delta$ were selected to provide a range of possible sampling points and a wide variable perturbation. The work done in King and Perera (2010) showed that little was gained by averaging results from experiments using different number of levels and different $\Delta$ values.

#### 4.4.1. Individual input variable experiments

Tables 3–6 present the $\mu$, $\mu^*$ and $\sigma$ results of the individual variable experiment considering the 14 input variables given in Table 2. The extensive numerical results given in Tables 3–6, are summarised by importance ranking in Table 7. Importance ranks are based on $\mu^*$ which is not subject to cancelling out that can occur in $\mu$. Rank 1 refers to the variable with the greatest $\mu^*$ value, i.e. the model and its output are most sensitive to that variable. Table 7 shows the variable ranks based on the $\mu^*$ and $\sigma$ indices for all climate scenarios with colour shading that highlight the top six ranked variables.

The equal but opposite $\mu$ and $\mu^*$ indices for both thresholds (Tables 3–6) indicate that they have an inverse monotonic input to output behaviour. When the thresholds are increased (i.e. become more strict), the yield estimate decreases. Alternatively, the yield estimate increases when the thresholds are lessened, i.e. become less strict.

The two most important input variables in all scenarios over all simulation lengths (except 20 year scenario 1) are the supply reliability and the minimum storage thresholds (see Table 7). The

**Table 6**
Morris method importance indices for individual input variables – 77 year scenarios.

| Morris index | Variable | Scenario | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| $\mu$ | Relative position 1 | −153 | −144 | −136 |
| | Relative position 2 | −82 | −111 | −239 |
| | Relative position 3 | −96 | −104 | −136 |
| | Percentage restrictable 1 | 124 | 55 | 42 |
| | Percentage restrictable 2 | 76 | 125 | 198 |
| | Percentage restrictable 3 | 61 | 143 | 41 |
| | Upper RRC curvature | −153 | −282 | −236 |
| | Upper RRC position | 166 | −173 | −113 |
| | Lower RRC curvature | 155 | 310 | 242 |
| | Lower RRC position | 251 | 276 | 204 |
| | Base demand | −1184 | −1143 | −1114 |
| | Target curves | −734 | −343 | −541 |
| | Minimum level threshold | −11132 | −13697 | −13299 |
| | Supply reliability threshold | −2816 | −5147 | −4992 |
| $\mu^*$ | Relative position 1 | 176 | 163 | 172 |
| | Relative position 2 | 82 | 133 | 263 |
| | Relative position 3 | 96 | 164 | 136 |
| | Percentage restrictable 1 | 132 | 130 | 166 |
| | Percentage restrictable 2 | 123 | 243 | 220 |
| | Percentage restrictable 3 | 112 | 229 | 129 |
| | Upper RRC curvature | 722 | 947 | 956 |
| | Upper RRC position | 963 | 1080 | 1129 |
| | Lower RRC curvature | 156 | 403 | 378 |
| | Lower RRC position | 257 | 276 | 206 |
| | Base demand | 1184 | 1143 | 1114 |
| | Target curves | 837 | 827 | 993 |
| | Minimum level threshold | 11132 | 13697 | 13299 |
| | Supply reliability Threshold | 2816 | 5147 | 4992 |
| $\sigma$ | Relative position 1 | 372 | 270 | 327 |
| | Relative position 2 | 215 | 268 | 954 |
| | Relative position 3 | 279 | 363 | 299 |
| | Percentage restrictable 1 | 232 | 246 | 383 |
| | Percentage restrictable 2 | 219 | 571 | 532 |
| | Percentage restrictable 3 | 237 | 395 | 288 |
| | Upper RRC curvature | 1193 | 1359 | 1377 |
| | Upper RRC position | 1294 | 1359 | 1534 |
| | Lower RRC curvature | 318 | 645 | 654 |
| | Lower RRC position | 407 | 463 | 329 |
| | Base demand | 809 | 1009 | 1041 |
| | Target curves | 777 | 1294 | 1715 |
| | Minimum storage threshold | 4077 | 6389 | 6692 |
| | Supply reliability threshold | 4920 | 7372 | 7495 |

importance of these thresholds is expected as they directly influence the performance of the system by defining system failure.

The top six variable importance measure rankings ($\mu^*$) and the non-linearity/interaction rankings ($\sigma$) in Table 7 are mostly the same, however in different orders. These variables are: the two threshold variables already mentioned, the two upper RRC variables, the target curve variable and the base demand. The remaining variables do not show notable $\mu^*$ ranking patterns in Table 7 and consistently have a low importance measure (see Tables 3–6), showing negligible importance. Strong non-linearity and/or interaction effects were detected for most variables, where $\sigma$ is often greater than $\mu^*$, i.e. the spread of the EEs is greater than the mean of the EEs. The two security criteria thresholds are the top two $\sigma$ rankings in Table 7, whose $\sigma$ values are significantly different to the remaining variables for all scenarios (see Tables 3–6). The upper RRC curvature and position variables also show high $\sigma$ for most scenarios.

The $\mu^*$ ranking of the threshold variables reflect which threshold is most critical within each climate scenario. The supply reliability threshold is critical when the simulation length is 20 years, except for scenario 3. Observation of the 20 year scenario 3 streamflow sequence shows a large and severe drought is present in the sequence which produces a rapid system drawdown, triggering the minimum storage threshold. The minimum storage threshold is the critical threshold for all 40, 60 and 77 year scenarios, except for the 40 year scenario 4; which does not trigger minimum storage threshold due to the absence of a significant storage drawdown from the relatively constant streamflow of that scenario.

When the supply reliability threshold has $\mu^*$ ranked 1 (i.e. supply reliability threshold is the critical security of supply criteria), the two upper RRC variables (i.e. curvature and position) are ranked 3 and 4, or higher and have a $\mu^*$ that is considerably higher than the other variables. This is due to the position of the upper RRC defining when supply reliability threshold is triggered. Conversely, when the minimum storage threshold is critical, the individual RRC variables and target curve variable show low importance (see Tables 3–6).

Comparison of the SA results of the 20 year scenarios 2, 2b and 2c and also the three 77 year scenarios highlight the effect of climate variability on the importance of input variables. Having said that, it should be noted that the three 20 year scenarios consist of different sub-sequences from the 77 year historic record with approximately equal total streamflow volume, while the three 77 year scenarios that are simply shuffled sequence and therefore the same total streamflow volume. Table 7 shows that the supply reliability threshold is the critical security criteria for these three 20 year scenarios while the minimum storage volume threshold is critical for the 77 year scenarios. The lack of agreement from these two sets of scenarios is a result of correlation between the thresholds and RRC (discussed in the above paragraph).

To summarise, as the simulation length increases, a drought is more likely to be captured in the climate scenario making the minimum storage threshold critical. This causes the minimum storage threshold variable to be highly important, which in turn makes the RRC variables and the target curve variables not important.

### 4.4.2. Grouped input variable experiments

As mentioned earlier, two sets of grouped input experiments were conducted. The first set was based on three groups as given in Table 2. A 50 trajectory, eight level ($p = 8$), $\Delta = 4$ Morris design was used for this experiment, similar to the individual variable experiment. The Morris method indices are presented in Tables 8–11. The SA results given in Tables 8–11 shows that the yield estimate is sensitive to all 3 groups of variables. The security criteria is clearly the most important in all scenarios with $\mu^*$ an order of magnitude greater than the second most important, the RRCs group. The target curves show the lowest importance for all scenarios. All groups have interaction or non-linear effects, indicated by non-zero $\sigma$ results. The $\mu^*$ and $\sigma$ indices have a range of magnitudes across scenarios of the same length and across different simulation lengths, with no discernable pattern.

The second grouping experiment concerned seven groups of input variables, which are listed in Table 2. The difference of this grouping experiment from the previous grouping experiment is the disaggregation of the RRC group into five smaller groups. The same 50 trajectory, eight level ($p = 8$), $\Delta = 4$ Morris design was used. The results are given in Tables 12–15 for all scenarios. The non-zero $\mu^*$ results in these tables show that the yield estimate is sensitive to all groups. All groups show significant interaction or non-linear effects, indicated by non-zero $\sigma$ results. Table 16 gives the average $\mu^*$ indices of each variable group for each simulation length as well as the ranking of these averages, where rank 1 has the greatest $\mu^*$ value.

The $\mu^*$ indices given in Table 12–15 shows non-conclusive results regarding importance of variables to the total streamflow volume or the simulation length. However, when $\mu^*$ for the variable groups are averaged for each simulation length, as in Table 16, it can be seen that as the simulation length increases, the base demand $\mu^*$ index increase, whereas the $\mu^*$ indices for the upper RRC and the target curves decrease. Table 16 also shows that for

**Table 7**
Individual variable ranks from mean $\mu^*$ and standard deviation $\sigma$ for different climatic scenarios.

| Morris Index | Individual Input Variable | Scenarios | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 20 Year | | | | | | | 40 Year | | | | | 60 Year | | | | | 77 Year | | |
| | | 1 | 2 | 3 | 4 | 5 | 2b | 2c | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 |
| μ* | Relative Position 1 | 8 | 7 | 11 | 8 | 8 | 7 | 9 | 8 | 8 | 12 | 12 | 9 | 10 | 8 | 7 | 10 | 10 | 8 | 12 | 11 |
| | Relative Position 2 | 13 | 12 | 14 | 11 | 12 | 11 | 14 | 13 | 13 | 14 | 10 | 14 | 7 | 14 | 13 | 14 | 14 | 14 | 13 | 8 |
| | Relative Position 3 | 14 | 14 | 10 | 13 | 14 | 14 | 10 | 14 | 14 | 13 | 14 | 13 | 14 | 13 | 14 | 13 | 13 | 13 | 11 | 13 |
| | Percentage Restrictable 1 | 7 | 9 | 12 | 10 | 11 | 9 | 7 | 11 | 8 | 8 | 8 | 11 | 13 | 10 | 9 | 12 | 8 | 10 | 14 | 12 |
| | Percentage Restrictable 2 | 10 | 11 | 8 | 9 | 9 | 13 | 11 | 10 | 12 | 11 | 11 | 10 | 9 | 9 | 11 | 8 | 9 | 11 | 9 | 9 |
| | Percentage Restrictable 3 | 11 | 8 | 13 | 14 | 13 | 12 | 13 | 6 | 7 | 5 | 13 | 12 | 12 | 11 | 12 | 7 | 11 | 12 | 10 | 14 |
| | Upper RRC Curvature | 3 | 4 | 3 | 4 | 3 | 4 | 4 | 4 | 6 | 7 | 4 | 6 | 6 | 6 | 6 | 6 | 4 | 6 | 5 | 6 |
| | Upper RRC Position | 2 | 3 | 9 | 3 | 4 | 3 | 3 | 3 | 3 | 4 | 3 | 3 | 3 | 4 | 5 | 3 | 3 | 4 | 4 | 3 |
| | Lower RRC Curvature | 9 | 10 | 6 | 7 | 7 | 8 | 8 | 9 | 10 | 9 | 9 | 8 | 8 | 12 | 10 | 9 | 7 | 9 | 7 | 7 |
| | Lower RRC Position | 12 | 12 | 7 | 12 | 10 | 10 | 12 | 12 | 11 | 10 | 7 | 7 | 11 | 7 | 8 | 11 | 12 | 7 | 8 | 10 |
| | Base Demand | 6 | 6 | 4 | 6 | 6 | 6 | 6 | 7 | 5 | 3 | 6 | 4 | 4 | 3 | 3 | 4 | 6 | 3 | 3 | 4 |
| | Target Curves | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 6 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 6 | 5 |
| | Minimum Storage Threshold | 4 | 2 | 1 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Supply Reliability Threshold | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| σ | Relative Position 1 | 6 | 6 | 11 | 9 | 8 | 7 | 9 | 8 | 8 | 12 | 11 | 7 | 11 | 7 | 7 | 12 | 9 | 8 | 12 | 12 |
| | Relative Position 2 | 10 | 11 | 13 | 10 | 12 | 11 | 14 | 13 | 13 | 14 | 8 | 14 | 7 | 14 | 14 | 14 | 14 | 14 | 13 | 7 |
| | Relative Position 3 | 14 | 14 | 7 | 13 | 14 | 14 | 6 | 14 | 14 | 13 | 14 | 11 | 14 | 11 | 11 | 9 | 11 | 10 | 11 | 13 |
| | Percentage Restrictable 1 | 7 | 9 | 12 | 11 | 11 | 10 | 8 | 11 | 7 | 7 | 10 | 12 | 10 | 13 | 9 | 13 | 8 | 12 | 14 | 10 |
| | Percentage Restrictable 2 | 11 | 12 | 5 | 8 | 9 | 13 | 12 | 9 | 11 | 10 | 13 | 10 | 9 | 12 | 12 | 8 | 10 | 13 | 8 | 9 |
| | Percentage Restrictable 3 | 13 | 7 | 14 | 14 | 13 | 12 | 13 | 3 | 10 | 4 | 12 | 13 | 13 | 10 | 13 | 4 | 13 | 11 | 10 | 14 |
| | Upper RRC Curvature | 4 | 5 | 8 | 3 | 3 | 4 | 4 | 6 | 6 | 8 | 5 | 4 | 6 | 3 | 6 | 7 | 5 | 4 | 3 | 5 |
| | Upper RRC Position | 3 | 3 | 10 | 5 | 4 | 3 | 3 | 4 | 3 | 5 | 3 | 3 | 4 | 4 | 3 | 6 | 3 | 3 | 3 | 4 |
| | Lower RRC Curvature | 8 | 13 | 4 | 7 | 6 | 8 | 10 | 10 | 12 | 9 | 9 | 8 | 8 | 9 | 10 | 10 | 7 | 9 | 7 | 8 |
| | Lower RRC Position | 12 | 10 | 6 | 12 | 10 | 9 | 10 | 12 | 9 | 11 | 7 | 9 | 12 | 8 | 8 | 11 | 12 | 7 | 9 | 11 |
| | Base Demand | 9 | 8 | 3 | 6 | 7 | 6 | 7 | 7 | 4 | 3 | 6 | 5 | 3 | 5 | 5 | 3 | 6 | 5 | 6 | 6 |
| | Target Curves | 5 | 4 | 9 | 4 | 5 | 5 | 5 | 5 | 5 | 6 | 4 | 6 | 5 | 6 | 4 | 5 | 4 | 6 | 5 | 3 |
| | Minimum Storage Threshold | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 2 |
| | Supply Reliability Threshold | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 2 | 1 | 1 | 1 |

**Table 8**
Results of Group 1 Morris method experiment – 20 year scenarios.

| Morris index | Group | Scenario | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 2b | 2c |
| $\mu^*$ | RRCs | 6472 | 5751 | 1767 | 2263 | 2183 | 4187 | 3587 |
| | Target curves | 1736 | 2043 | 757 | 1128 | 729 | 2009 | 1915 |
| | Security criteria | 16616 | 26503 | 11985 | 10617 | 9767 | 22613 | 13650 |
| $\sigma$ | RRCs | 4548 | 5751 | 2398 | 1891 | 1606 | 2779 | 3571 |
| | Target curves | 1559 | 1907 | 659 | 1083 | 578 | 1312 | 1884 |
| | Security criteria | 4890 | 12205 | 6753 | 4101 | 4329 | 8261 | 5926 |

**Table 9**
Results of Group 1 Morris method experiment – 40 year scenarios.

| Morris index | Group | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu^*$ | RRCs | 2463 | 1559 | 2219 | 3345 | 1536 |
| | Target curves | 1132 | 1177 | 1265 | 1296 | 792 |
| | Security criteria | 16290 | 13418 | 14830 | 17715 | 11177 |
| $\sigma$ | RRCs | 3954 | 2002 | 3602 | 2920 | 1324 |
| | Target curves | 1656 | 2076 | 1861 | 1587 | 672 |
| | Security criteria | 12863 | 9378 | 10457 | 7574 | 4227 |

**Table 10**
Results of Group 1 Morris method experiment – 60 year scenarios.

| Morris index | Group | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu^*$ | RRCs | 1779 | 1561 | 1201 | 1344 | 1738 |
| | Target curves | 970 | 837 | 711 | 779 | 1005 |
| | Security criteria | 11594 | 11837 | 10642 | 11288 | 11705 |
| $\Sigma$ | RRCs | 2630 | 1448 | 937 | 1245 | 2423 |
| | Target curves | 1372 | 688 | 594 | 861 | 1426 |
| | Security criteria | 8353 | 3178 | 3513 | 6534 | 7617 |

**Table 11**
Results of Group 1 Morris method experiment – 77 year scenarios.

| Morris index | Group | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| $\mu^*$ | RRCs | 1522 | 1893 | 1561 |
| | Target curves | 835 | 1107 | 1304 |
| | Security criteria | 11612 | 15279 | 13269 |
| $\sigma$ | RRCs | 1530 | 1474 | 1632 |
| | Target curves | 650 | 1144 | 1868 |
| | Security criteria | 3123 | 6130 | 5820 |

the 20, 40 and 60 year simulation lengths, the security criteria, the upper RRC and target curves are ranked 1, 2 and 3, respectively.

The grouping experiments indicate that to improve the estimation of yield, the water authorities should focus studies, research

**Table 12**
Results of Group 2 Morris method experiment – 20 year scenarios.

| Morris index | Group | Scenario | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 2b | 2c |
| $\mu^*$ | Relative position | 397 | 205 | 181 | 211 | 270 | 126 | 342 |
| | Percentage restrictable | 318 | 308 | 88 | 243 | 155 | 168 | 180 |
| | Upper RRC | 5209 | 4107 | 1261 | 2180 | 1737 | 3194 | 2706 |
| | Lower RRC | 117 | 42 | 163 | 87 | 96 | 122 | 196 |
| | Base demand | 260 | 564 | 502 | 311 | 230 | 167 | 210 |
| | Target curves | 1462 | 1574 | 967 | 1212 | 558 | 1467 | 1654 |
| | Security criteria | 14102 | 22027 | 12095 | 8732 | 8379 | 20021 | 12140 |
| $\sigma$ | Relative position | 901 | 411 | 428 | 358 | 400 | 285 | 553 |
| | Percentage restrictable | 601 | 647 | 164 | 319 | 258 | 268 | 246 |
| | Upper curve | 4799 | 4122 | 1802 | 1998 | 1790 | 2602 | 2899 |
| | Lower curve | 292 | 159 | 375 | 213 | 218 | 275 | 313 |
| | Base demand | 599 | 1108 | 485 | 633 | 329 | 315 | 308 |
| | Target curves | 1415 | 1522 | 892 | 1324 | 608 | 1161 | 1525 |
| | Security criteria | 5169 | 11792 | 6727 | 4361 | 4565 | 8609 | 5476 |

**Table 13**
Results of Group 2 Morris method experiment – 40 year scenarios.

| Morris index | Group | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu^*$ | Relative position | 218 | 177 | 178 | 320 | 230 |
| | Percentage restrictable | 124 | 219 | 153 | 300 | 267 |
| | Upper curve | 1728 | 1319 | 1535 | 2390 | 1295 |
| | Lower curve | 244 | 171 | 206 | 247 | 140 |
| | Base demand | 522 | 521 | 429 | 327 | 947 |
| | Target curves | 1070 | 844 | 1009 | 1224 | 668 |
| | Security criteria | 17163 | 14433 | 15879 | 15797 | 10952 |
| $\sigma$ | Relative position | 290 | 235 | 280 | 377 | 373 |
| | Percentage restrictable | 245 | 457 | 290 | 353 | 393 |
| | Upper RRC | 2957 | 1733 | 2560 | 1989 | 1199 |
| | Lower RRC | 735 | 362 | 363 | 335 | 262 |
| | Base demand | 801 | 458 | 383 | 416 | 854 |
| | Target curves | 1407 | 930 | 777 | 1023 | 634 |
| | Security criteria | 11285 | 8262 | 9573 | 7721 | 5092 |

**Table 14**
Results of Group 2 Morris method experiment – 60 year scenarios.

| Morris index | Group | Scenario | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $\mu^*$ | Relative position | 223 | 245 | 247 | 132 | 216 |
| | Percentage restrictable | 140 | 280 | 251 | 163 | 153 |
| | Upper RRC | 1466 | 1038 | 932 | 1268 | 1465 |
| | Lower RRC | 169 | 201 | 339 | 175 | 127 |
| | Base demand | 508 | 1099 | 917 | 456 | 495 |
| | Target curves | 770 | 680 | 880 | 875 | 906 |
| | Security criteria | 12014 | 11938 | 10824 | 11706 | 12143 |
| $\Sigma$ | Relative position | 358 | 341 | 384 | 208 | 351 |
| | Percentage restrictable | 318 | 324 | 309 | 323 | 268 |
| | Upper RRC | 1797 | 1000 | 943 | 1388 | 1868 |
| | Lower RRC | 299 | 371 | 416 | 332 | 277 |
| | Base demand | 465 | 859 | 737 | 404 | 401 |
| | Target curves | 875 | 637 | 650 | 863 | 929 |
| | Security criteria | 7282 | 2982 | 4127 | 6999 | 7503 |

and expenditure of resources into the security criteria, the upper RRC and the base demand variables.

### 4.5. Discussion

The findings drawn from this study and given in following discussion are specific to the Barwon urban water supply system.

As found with the individual variable experiment, the most important input variables in all scenarios over all simulation lengths were the supply reliability and the minimum storage thresholds. The upper RRC position, upper RRC curvature variables, target curves and base demand also showed importance across most scenarios.

A correlation in the importance indices of input variables was identified. When the supply reliability threshold is the critical security of supply criteria, the upper RRC curvature and position variables are also important. When the minimum storage threshold is critical, the remaining variables show non-conclusive impor-

**Table 15**
Results of Group 2 Morris method experiment – 77 year scenarios.

| Morris index | Group | Scenario | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| $\mu^*$ | Relative position | 217 | 325 | 213 |
| | Percentage restrictable | 265 | 238 | 221 |
| | Upper RRC | 922 | 1228 | 1152 |
| | Lower RRC | 162 | 408 | 255 |
| | Base demand | 1009 | 943 | 1306 |
| | Target curves | 654 | 544 | 860 |
| | Security criteria | 11529 | 15037 | 13016 |
| $\sigma$ | Relative position | 330 | 424 | 330 |
| | Percentage restrictable | 314 | 301 | 269 |
| | Upper RRC | 823 | 1308 | 1152 |
| | Lower RRC | 340 | 632 | 424 |
| | Base demand | 850 | 909 | 1802 |
| | Target curves | 602 | 646 | 1054 |
| | Security criteria | 3335 | 6408 | 5937 |

tance. This correlation shows that the importance of input variables changed when simulated under different climate scenarios and different simulation lengths. This finding could only be made with the use of multiple climate scenarios. Moreover, it is an important finding as it highlights that using only one climate scenario in the estimation of yield and other planning studies can lead to the optimisation of a set of system policy variables that may not be suitable for another simulation period or different climate scenario.

Most input variables showed a non-monotonic relationship with the yield estimate, which means that a positive change to the input variable resulted in a positive or a negative change in the yield estimate, indicating second-order or interaction effects. The notable exceptions were the supply reliability and minimum storage thresholds which showed a negative monotonic relationship with the yield estimate, i.e. a positive change to the threshold(s) causes a decrease in the yield estimate.

When grouped, the most important group of input variables was always the security criteria. In the grouping experiments it was seen that the importance of the base demand increased and the importance of the upper RRC and target curves decreased, as the simulation length increased.

The change of importance over different simulation lengths and the correlation caused by different climate scenarios of the same length illustrate that using only one climate scenario to estimate the yield of the Barwon system will result in a dependence on and therefore an optimisation of variables' states and values that will not be appropriate for all other scenarios. For instance, using the entire available dataset (77 years) for the Barwon system shows that the yield estimate is sensitive and therefore heavily influenced by the minimum storage threshold and somewhat on the base demand. When the system policy variables are optimised for this scenario, they may not be suitable for another scenario, especially the 20 year scenarios when the estimation of yield is influenced strongly by the supply reliability threshold and the upper RRC curvature and position variables.

## 5. Conclusions

Presented in this paper is an application of the Morris method of sensitivity analysis to determine the individual and groups of input variables that are most important in estimating the yield of urban water supply systems. This study considered the Barwon urban water supply system in Australia. The sensitivity analysis was based on a climate scenario framework where 20 climate sequences were selected from within the available historic data over four simulation lengths. Multiple scenarios of each simulation length were either selected based on the total streamflow volume entering the six reservoirs of the Barwon system, or generated by a shuffling (or recycled) approach. The sensitivity analysis using the Morris method was performed on all scenarios considering individual variables and two different groupings of variables.

The individual and grouping experiments showed the security criteria thresholds to be the most important variables, with upper restriction rule curve variables also showing notable importance. The individual variable experiment showed that when the supply reliability threshold was the most important variable (i.e. the critical security criteria threshold), the upper RRC curvature and position variables were also important. However, when the minimum storage threshold was critical, the remaining input variables showed non-conclusive importance. The averaged results of the second grouping experiment (i.e. with more sub-groups for RRCs) showed that the importance of the base demand increased as the simulation length increased while the importance of the upper RRC and target curves decreased.

The results given in this paper demonstrate that using a single climate scenario in the estimation of yield can give unrepresentative outcomes for the yield estimate and also of the possible behaviour of the system under a different climate scenario. Further investigation into the sensitivity of estimation of yield of an urban water supply system to the inputs and climate variability will be conducted using a high detailed and quantitative sensitivity analysis technique, such as the variance based Fourier Amplitude Sensitivity Test. This paper provides a basis to extend the study to other water supply systems, which when compared could be used to develop a generic understanding of urban water supply system behaviour. Research can also be undertaken into characterising the climate sequences and how a particular characteristic affects system behaviour. The framework in this paper can also be used on other models using climate time-series.

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**Table 16**
Average $\mu^*$ and associated ranking for different simulation lengths in Group 2 experiment.

| Group | 20 Year scenarios | | 40 Year scenarios | | 60 Year scenarios | | 77 Year scenarios | |
|---|---|---|---|---|---|---|---|---|
| | Average $\mu^*$ | Rank | Average $\mu^*$ | Rank | Average $\mu^*$ | Rank | Average $\mu^*$ | Rank |
| Relative position | 247 | 5 | 225 | 5 | 213 | 5 | 252 | 6 |
| Percentage restrictable | 209 | 6 | 213 | 6 | 197 | 7 | 241 | 7 |
| Upper RRC | 2913 | 2 | 1653 | 2 | 1234 | 2 | 1101 | 2 |
| Lower RRC | 118 | 7 | 202 | 7 | 202 | 6 | 275 | 5 |
| Base demand | 321 | 4 | 549 | 4 | 695 | 4 | 1086 | 3 |
| Target curves | 1271 | 3 | 963 | 3 | 822 | 3 | 686 | 4 |
| Security criteria | 13928 | 1 | 14845 | 1 | 11725 | 1 | 13194 | 1 |

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